In the Drawings

Replacement drawings Figs. 1-6 are submitted herewith to identify prior art (see Fig. 1) and to conform the drawings to include reference numeral designations 20, 30, 40, 50, 60 and 70 that were added to the specification. No new matter has been added.

REMARKS

This preliminary amendment is being filed to clarify the specification, which is an English language translation, and to conform the drawings to the clarifications made to the specification. No new matter has been added.

Favorable action is respectfully solicited.

Respectfully submitted,

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Attorney Docket No: 100717-574US

Rec'd PCT/PTO 11 FEB 2005

10/511231

MARKED-UP SPECIFICATION

METHOD AND COMPUTER SYSTEM FOR DESIGNING EXPERIMENTS

FIELD OF THE INVENTION

The present invention relates generally to~~-a~~ method and ~~a computer~~ system for designing experiments~~, and to a corresponding computer program product.~~ using a computer, and more particularly, using a computer to design experiments where the processing performed by the computer to design experiments includes evaluation of experimental data and data filtering.

BACKGROUND OF THE INVENTION

~~From~~In the prior art, it is known to design experiments ~~by means of~~using statistical experiment ~~designing~~design methods. Such ~~designing~~design methods are used, *inter alia*, to determine, with a minimum number of experiments, an empirical process model for the relationship between ~~the~~ controlled variables and influencing variables in a process and for the resulting product properties and process properties. Such statistical experiment ~~designing~~design methods can be ~~carried out~~performed, for example, using the "STAVEX" (STAtistical experiment designing with EXpert system ~~produced by~~, manufacturer AICOS ~~Technologie~~Technologies, Switzerland) computer ~~program. A further commercially available computer program for experiment designing is the~~software program and software sold under the name "Statistica®" ~~program made~~ by StatSoft (Europe) GmbH, Germany.

~~In~~Various, different prior art experiment design techniques exist in the field of statistical experiment ~~designing, various experiment designing types are distinguished~~

~~in the prior art. In particular, a distinction is made between the~~ design. All statistical experiment design methods originate from the classic~~,~~, fully factorial method ~~and modern methods according to Taguchi or Shainin.~~ ~~The classic, fully~~ The factorial method ~~is the origin of all statistical experiment designing methods. It is based on a comparison of all~~compares all of the quality-conditioned factors with one another by analogy with variance analysis. ~~Numerous variants have been produced over~~ Over the course of the last few decades, numerous variants of the factorial method have been developed and validated in research and development laboratories.

Modern experiment design methods according to Taguchi or Shainin are distinguishable from the classic, fully factorial methods. The Shainin ~~DOE (~~Design of Experiment~~)~~ ("DOE") method is a suitable ~~process for process~~ optimization process because it isolates what are ~~referred to~~known as "strong" influencing variables and ~~investigates them for~~performs processing to determine their relevance and dependence. The Taguchi DOE is based on ~~preceding,~~prior art fractional factorial, orthogonal experiment designs. ~~Because of the~~ As pre-selecting the most important influencing variables achieves drastic savings in terms of experiment runs ~~by preselecting the most important influencing variables, this~~necessary, the Tagauchi technique is a rapid and relatively economic method of designing experiments and processes.

Further known statistical experiment design ~~types~~techniques of the fractional factorial experiment ~~designs,~~design type include Plackett-Burmann experiment designs, central composite designs, ~~box~~Box-Behnken experiment designs, D-optimal designs, mixed designs, balanced block designs, Latin squares, and desperado designs (~~cf. in this respect also~~see e.g. Eberhard Scheffler, ~~Statistische~~Statische Versuchsplanung

~~and – auswertung; ["statistical experiment design and evaluation"];~~und- Auswertung, Deutscher Verlag für Grundstoffindustrie, Stuttgart, 1997).

~~Further~~Additional methods for designing experiments are also known from Hans Bendemer, "Optimale Versuchsplanung" [Optimum experiment design], Reihe Deutsche Taschenbücher (DTB, Volume 23, and ISBN 3-87144-278-X) and Wilhem Kleppmann, Taschenbuch Versuchsplanung, "Produkte und Prozesse optimieren" [Optimize products and processes], 2nd expanded edition, ISBN: 3-446-21615-4. These methods are often used in practice for reasons of cost.

The disadvantage with known statistical methods for designing experiments is that the processing associated with experiment ~~designing~~design and modelling is ~~carried out~~performed without ~~taking into account~~accounting for additional knowledge ~~so that~~. Consequently, under certain circumstances, no suitable optima are found and the reliability of the results and statements ~~which are~~ generated is questionable. A further significant disadvantage of ~~previously known~~prior art methods for designing experiments is that ~~when there is~~, where a large number of influencing variables need to be taken into account, ~~said~~the prior art methods become too extensive. In addition, with respect to certain experimental systems, for example in catalysis or active ingredient research, the target function is often heavily "fractured" and ~~is~~, therefore, is difficult to capture with statistical methods.

WO 00/~~15344~~15341, incorporated by reference herein, discloses a method for developing solid catalysts for heterogeneous catalysed reaction processes, which is based on parallelized testing according to evolutionary methods. Corresponding methods which operate in an evolutionary way are also known from WO 00/43411, J.

chem. Inf. Compute. Sci. 2000, 40, 981-987 "Heterogeneous Catalyst Design Using Stochastic Optimization Algorithms" and from Applied Catalysis A: General 200 (2000) 63-77 "An evolutionary approach in the combinatorial selection and optimization of catalytic materials", each of which incorporated by reference herein.

In addition, ~~US 6,009,379~~U.S. Patent No. 6,009,379, incorporated by reference herein, discloses a method for controlling a manufacturing process by means of an efficient experimental design. ~~Here~~ According to this patent, test points are distributed uniformly on a multidimensional spherical surface ~~in order to be able to weight~~so that the individual manufacturing parameters can be weighted uniformly.

~~Figure~~FIG. 1 shows a block diagram of a ~~system, known from the~~ prior art~~,~~ system 20 for ~~carrying out~~performing screening experiments, such as ~~is~~may be used ~~in particular~~ in the fields of catalysis and material and active ingredient research. ~~The system~~ It is to be understood that each of the functional blocks of the system 20 described below as performing data processing operations, as well as functional blocks of the systems described below and shown in the drawings as constituting embodiments of the present invention, constitutes a software module or, alternatively, a hardware module or a combined hardware/software module. In addition, each of the modules suitably contains a memory storage area, such as RAM, for storage of data and instructions for performing processing operations. Alternatively, instructions for performing processing operations can be stored in hardware in one or more of the modules.

Referring to FIG. 1, the system 20 includes a substance library~~, that is to say what is referred to~~ module 1, such as a combinatorial library ~~1 and~~module, coupled to

an experiment set-up ~~2 for carrying out~~module 2. The module 2 is coupled to an experiment data module 3 and a data-driven optimizer 4. The optimizer 4 also is coupled to the library module 1. The module 2 performs high throughput screening ("HTS") or high speed experimentation ("HSE") experiments. Such screening experiments ~~are~~ typically are used for identifying active ingredients, catalysis research (homogeneous and heterogeneous), materials research and identification of optimum reaction conditions in chemical, biochemical or biotechnical systems. The optimizer 4 is a black-box optimizer which operates based on a data-driven model or on an evolutionary algorithm. The optimizer 4 does not have a priori knowledge of the structure and interactions concerning experiment design. The optimizer 4, instead, is restricted to the evaluation of the experiment data for purposes of selecting experiments stored at the combinatorial library module 1. The black-box optimizer 4 is implemented, for example, by means of genetic algorithms, evolutionary algorithms or strategies, neural networks or other data-driven model approaches which rely on stochastic or deterministic optimization structures or optimization structures which are a combination of both the former and latter.

~~A~~In operation, the experiment set-up module 2 usually performs processing on a plurality of experiments ~~are usually carried out in parallel in such an experiment set-up 2. The experiment results are output in the form of a file 3. This output data, or some of it, is at the same time the input data for an~~. The module 2 provides experimental results in the form of a data file to the experiment data module 3. At the same time, the module 2 provides the experimental result data, or at least a portion thereof, as input data to the data-driven optimizer 4. The ~~optimizer 4 is what is referred to as a black-box~~

~~optimizersr, that is to say an optimizer which is based on a data-driven model or on an evolutionary algorithm. A priori knowledge of the structure and/or interactions is not present in the optimizer 4; instead said optimizer 4 is restricted to the evaluation of the data as such in order to make a selection of experiments from the combinatorial library 1.The optimizer 4 typically uses the~~ experiment data ~~3 composed of~~in the module 3 includes influencing variables~~(~~, such as attributes, factors, structure features, descriptors, physical variables~~,~~ and properties of materials~~)~~, and data relating to the effect ~~of~~ these variables have on ~~what are referred to as targets (~~target variables~~), in order~~. The optimizer 4 in performing its processing typically uses the experiment data stored in the module 3 to define an optimum search direction within the space of the ~~targets.~~target variables.

~~Such a black-box optimizer 4 is implemented, for example, by means of:~~

- ~~genetic algorithms,~~
- ~~evolutionary algorithms or strategies,~~
- ~~neutral networks or~~
- ~~other data-driven model approaches which rely on stochastic or deterministic optimization structures or optimization structures which are a combination of both of these.~~

A common disadvantage of ~~such~~ systems ~~known from~~similar to the prior art system 20 is that a priori information cannot have an influence, or can only have a restricted influence, in the black-box optimizer 4, ~~and corresponding~~such that search strategies often converge slowly~~,~~ or converge on unsuitable suboptima. ~~Such methods which are known from the~~ Consequently, prior art ~~are therefore~~methods often are inefficient in terms of the expenditure of time and ~~the~~ financial outlay. ~~With~~ In addition, where experiment design techniques are based on evolutionary algorithms, there is ~~also~~

~~the~~a risk ~~of~~that the expenditure and outlay ~~being~~is higher when the optimizer is used to reach the optimum than when a rational or statistical procedure is used.

~~The invention is therefore based on the object of providing an improved~~Therefore, there exists a need for a method and system for designing ~~experiments and a corresponding computer system and computer program product.~~

~~The object on which the invention is based is respectively achieved by means of the features of the independent patent claims. Preferred embodiments of the invention are given in the dependent patent claims.~~

~~The subject matter of the invention is a method for designing experiments for achieving an optimization goal having the following steps:~~

~~A) selection of at least a first experiment from an experimental space by means of a data-driven optimizer in a computer unit,~~

~~B) inputting of experimentally determined experiment data of the first experiment in at least one meta layer into a computer unit,~~

~~C) use of at least one meta layer for the evaluation of the experiment data,~~

~~D) inputting of the experimentally determined experiment data of the first experiment into the data-driven optimizer,~~

~~E) influencing of the data-driven optimizer by the result of the evaluation in the meta layer and checking the goal achieved,~~

~~F) selection of at least a second experiment from the experimental space by means of the data-driven optimizer,~~

~~G) repetition of steps B) to E) for the data of the second experiment,~~

~~and~~

~~H) stopping the hexation on achieving the goal or repeating steps A) to F) for at least a third or subsequent experiments until the goal has been achieved.~~

~~The method is repeated until the optimization goal has been achieved or until it is concluded that it may not be possible to achieve the optimization goal. The method can be terminated automatically or by the user. The optimization goal may be to reach certain evaluation characteristic numbers for the experiments. The characteristic numbers may, for example, be yield selectivities, space time yields, costs, physical properties, action mechanisms, derived properties, etc. It is also possible to evaluate the experiments using a plurality of characteristic numbers.The invention permits knowledge for influencing the black-box optimizer to be integrated with the objective of speeding up the convergence and/or ensuring convergence at a suitable optimum as well as~~experiments using a computer based system which improves convergence speed and ensure convergences at a suitable optimum while also increasing the reliability of the results.~~The knowledge may be known here a priori as prior knowledge and/or may be supplemented~~

SUMMARY OF THE INVENTION

In accordance with the present invention, method and system for designing experiments using a computer based system involves using knowledge associated with experimentation to influence processing at a data-driven optimizer. The knowledge includes a prior knowledge and supplementary knowledge obtained from continuously ~~by~~ evaluating ~~experiments which have been carried out~~ previously performed experiments.

~~Additional knowledge is preferably generated here in the form of "rules", in particular~~In a preferred embodiment, a computer based system for designing experiments includes a meta layer module which uses a priori and supplementarily obtained knowledge to influence processing operations at an optimizer, thereby effectively tuning the optimizer. The knowledge preferably includes rules associated with interactions, such as rules relating to ~~the~~ structure-interaction with data mining and

other methods.~~ These~~ The rules can be integrated in the processing the optimizer performs for designing ~~of the experiment,~~experiments at to influence the optimizer processing before, during or after an optimization processing step, or even continuously~~, the data driven optimizer being influenced correspondingly. A meta layer is provided for influencing the data-driven optimizer~~.

~~The black-box optimizer is tuned by using such a meta layer. In this context, the meta layer is not restricted to one method but rather may contain a combination of various methods. Possible methods are:~~

~~— neural networks,~~
~~— hybrid model,~~
~~— rigorous models,~~

~~— data mining methods, for example~~In a preferred embodiment, the meta layer module can perform processing corresponding to the processing models associated with a neural network, a hybrid model, a rigorous model and data mining methods. The data mining methods can include a decision tree ~~methods,~~method, a general separation ~~methods,~~method, a subgroup search ~~methods,~~method, a general partition ~~methods,~~method, a cluster ~~methods,~~method, an association rule ~~generators~~generator and a correlation ~~methods~~method.

~~The method of operation of~~In a preferred embodiment, the processing at the optimizer ~~can be~~is influenced ~~directly here by intervening in the method of operation of~~by direct intervention with the processing operations performed by the optimizer, or indirectly by filtering the data which ~~form~~forms the basis for the optimization processing performed by the optimizer.

~~According to one~~In another preferred embodiment~~ of the invention, methods~~, a method for influencing the optimizer ~~are used which tune~~tunes the optimizer and/~~or~~ the optimization process.~~ Such methods~~ The tuning method can include, for example, a

subgroup search ~~methods or~~method, correlation ~~analyses or~~analysis and attribute statistics in the case of rule generators.

~~According to one~~In a further preferred embodiment~~of the invention, further meta layers are provided which improve the respectively preceding meta layer or intervene in the~~, the inventive system includes a plurality of meta layer modules, such that processing is improved in a preceding meta layer, intervention can occur in a preceding meta layer or layers and~~/or also intervene directly~~ direct intervention can occur in the black-box optimization ~~process of the first level~~processing performed at the optimizer.

~~According to~~In still a further preferred embodiment of the invention, the intervention positions in the original optimization process and the methods or combinations of methods ~~which are~~ used in the meta layer~~ or layers can be~~(s) are varied in each optimization step.~~ The selection of~~ In addition, selecting suitable methods for generating optimum rules can be ~~carried out~~performed automatically~~ here~~.

~~According to one~~In another preferred embodiment~~ of the invention~~, the optimizer is influenced by a re-evaluation of ~~the~~ experiment data~~. For example, the experiment data itself can~~ which already ~~contain~~contains an evaluation~~ by virtue of the fact that~~. The experiment data can include an evaluation where appropriate experiment data, ~~for example the~~such as yield data, is determined directly by ~~experimental means. In this case, the~~experimentation. The re-evaluation can be ~~carried out~~performed by filtering the yield data~~, for example by virtue of the fact that~~. The method of filtering utilized is based on rules or other relationships which are determined based on an analytical method of processing experiment data, for example, processing methods associated with neural networks and data mining methods. Data filtering further increases the weighting of particularly good yields ~~are given a heavier~~and further reduces the weighting ~~by means of the data filtering, and~~of particularly bad yields~~ are given a lighter weighting by means of the data filtering. A~~, thereby achieving a more rapid convergence of the experiment sequence~~ can be achieved by the means of this type of data filtering~~.

~~A corresponding procedure can be adopted if~~In an alternative embodiment where the experiment data does not directly contain an experimentally determined evaluation, but rather the evaluation is determined only by ~~means of~~ calculations which follow the experiment~~. In this case~~, filtering or weighting is performed not on data which is determined experimentally but rather on evaluations which are determined by calculation.

~~The method of filtering results here from rules or other relationships which have been found on the basis of an analytical method of the experiment data, for example by means of neutral networks or data mining methods or other methods.~~

~~According to~~In a further preferred embodiment, the optimizer processing is influenced by reducing, enlarging ~~and/~~or displacing the experimental space.

~~According to~~In still a further preferred embodiment, the filtering ~~is carried out by means of preselection and/or~~can include pre-selecting and weighting of the experiment data. Particularly "bad" experiment data, ~~that is to say~~in other words, experiment data ~~which has been~~ recognized as unsuitable by, for example, a rule generator, is ~~preselected~~pre-selected and eliminated from the experimental space. In addition, if the rule generator determines that corresponding parameters are irrelevant, entire columns or rows can also be eliminated from ~~the~~an experiment data matrix ~~if the corresponding parameters have been recognized as irrelevant by the rule generator. As a result~~, thereby reducing the experimental space ~~is reduced, which~~and, in turn, considerably ~~reduces~~reducing the overall expenditure in terms of processing time.

The weighting of the experiment data can ~~be weighted in that experiment data which is recognized as being~~include duplicating particularly relevant ~~is duplicated~~experiment data a single time or repeatedly in the experiment data matrix. Alternatively, the weighting can include introducing a weighting coefficient ~~can be introduced~~.

~~According to one~~In a further preferred embodiment of the invention, the ~~black-box optimizer contains what are referred to as core modules or core operators as well as a model for selecting new test points.~~optimizer includes at least one core operator module and a module for selecting new test points. The method of operation of the optimizer is then influenced by influencing at least one of the core ~~module or~~ modules and/~~or~~ the module for selecting new test points based on relationships ~~which have been~~ recognized by, for example, a rule generator.

~~DETAILED DESCRIPTION~~ BRIEF DESCRIPTION OF THE DRAWINGS

~~Preferred embodiments~~Other objects and advantages of the present invention will be ~~explained in more detail below with reference to the drawings,~~apparent from the following detailed description of the presently preferred embodiments, which description should be considered in conjunction with the accompanying drawings in which:

~~Figure 1 shows a block diagram representing a system for designing experiments which is known from the prior art,~~

FIG. 1 is a block diagram of a prior art system for designing experiments.

~~Figure~~FIG. 2 ~~shows~~ is a block diagram of an embodiment of a system for designing experiments according to the present invention ~~for designing experiments,~~.

~~Figure~~FIG. 3 ~~shows~~ is a block diagram of an embodiment of ~~the~~a system for designing experiments according to the present invention ~~for designing experiments with a~~including re-evaluation of the experiment data~~,~~.

~~Figure 4 shows~~FIG. 4 is a block diagram of an embodiment of ~~the~~a system for designing experiments according to the present invention ~~for designing experiments with preselection and/or~~including pre-selection and weighting of the experiment data~~,~~.

~~Figure 5 shows~~FIG. 5 is a block diagram of an embodiment of ~~the~~a system for designing experiments according to the present invention ~~for designing experiments with~~including influencing ~~of~~ the selection of new test points ~~of the optimizer,~~at the optimizer.

~~Figure 6 shows~~

FIG. 6 is a block diagram of an embodiment of ~~the~~a system for designing experiments according to the present invention ~~for designing experiments with influencing of the core module or core modules of the optimizer.~~including influencing a core module of the optimizer.

~~BRIEF DESCRIPTION OF THE DRAWINGS~~ DETAILED DESCRIPTION OF PREFERRED EMBODIMENTS

FIG. 2 shows in block diagram form an embodiment of a system 30 for designing experiments in accordance with the present invention. Like reference numerals are used herein to describe system components having substantially similar, and preferably identical, structure and operation as described previously.

~~The system for designing experiments in Figure 2 is based on~~Referring to FIG. 2, the system 20 includes a combinatorial library 5 which is formed based on ~~the basis of~~ the peripheral conditions ~~given by means of an experimental space. From this combinatorial library 5, an~~corresponding to an experimental space. An experiment set-up module 7 is coupled to the library 5, an experiment data module 8 and a meta layer module 9. The module 9 includes an optimizer 6 and is coupled to the library 5. In operation, the optimizer 6 selects one or more experiments from the combinatorial library 5, which are then ~~carried out~~performed in ~~an~~the experiment set-up module 7, for example, by means of a high throughput screening or high speed experimentation

experiment method. The ~~corresponding~~ experiment data ~~is output in the form of a file 8.In the system for designing experiments, a meta layer 9 is provided for the optimizer 6. The meta layer 9 is used to influence the optimizer 6~~generated at the module 7 is provided in the form of a data file to the experiment data module 8.

The meta layer module 9 influences processing at the optimizer 6 by taking into account a priori knowledge or knowledge acquired while the experiment is ~~being carried out. Knowledge, for example in the form of rules or in the form of trained neural networks, can be acquired here continuously by the evaluation of files 8.~~performed. In a preferred embodiment, the optimizer 6 continuously evaluates the data stored as data files in the module 8 to acquire knowledge in the form of rules or trained neural networks. The meta layer ~~9~~module 9, therefore, complements and influences processing at the ~~data-driven~~ optimizer 6 by ~~means of~~providing additional knowledge ~~in order to speed up~~to the optimizer 6, thereby hastening convergence of the experiment series.

The meta layer module 9 ~~therefore~~ also permits improvement of the convergence speed of a black-box optimization method, which is implemented in the optimizer 6, ~~to be improved~~ by integrating prior knowledge and/~~or~~ rule structures. This integration can be ~~carried out~~performed in various ways, ~~for example~~such as by ~~means of~~: A) information-supported additional selection of the test ensembles, ~~i.e. restriction~~which uses the rules found with data mining to restrict the portion of the combinatorial library 5 to be tested ~~by means of the rules found with data mining and no~~and does not involve intervention ~~into~~in the processing performed at the optimizer 6; B) selective weighting of the optimization steps in the direction of library areas identified as optimum, ~~i.e.~~in

other words, intervention into the search method of the optimizer~~, C~~ 6; and C) tuning ~~of~~ the selection rules of the black-box optimization methods, ~~i.e.~~which involves direct intervention into the evaluation method of the optimizer 6 or modification of the evaluation variables before ~~being input into~~they are provided to the optimizer~~The~~ 6. In a preferred embodiment, the forms of intervention A, B and C may ~~basically also be carried out~~be performed in combination~~, i.e.~~. For example, in an optimization step~~ it is also possible for~~, the interventions ~~to be carried out with~~can include A and B, B and C, A and C, or A and B and C. The intervention positions and intervention combinations as well as the methods ~~used~~performed in the meta layer module 9 may change from optimization step to optimization step. The interventions ~~can~~ also can be ~~carried out~~performed from subsequent meta ~~layers~~layer modules included in the experiment design system.

When optimizing by means of statistical experiment design, the ~~procedure~~processing performed is similar to ~~the use of~~that performed by a black-box optimizer~~, that is to say here too~~. The meta layer module 9 performs an intervention ~~is carried out~~ in the optimization process ~~by means of the meta layer~~ in one or more of the forms described above. For example, ~~the integration of~~ prior knowledge is ~~carried out by virtue of the fact that~~integrated when the influencing variables are selected, such that their field of validity and~~/or~~ additional restrictions ~~of~~on the field of validity are included in the combination of influencing variables.

Further information on influencing variables may be included for the sequential statistical designing of experiments by using data mining methods or other methods described above~~,~~ and ~~integrated~~integrating them into the processing for designing of

experiments. For example,~~that is to say~~ the experimental space ~~is~~may be changed on the basis of the additional information after ~~the first, second ..., n-th path, respectively.~~an experiment design processing sequence is performed. The change is ~~carried out~~performed by~~a)~~ adding or removing influencing variables~~b)~~, changing the fields of validity of the individual influencing variables or combined influencing variables~~c)~~, or a combination of ~~a)~~the former and ~~b)~~latter.

It is particularly ~~advantageously here~~advantageous that ~~"~~prior art classic~~"~~ methods for designing experiments~~which are known from the prior art~~ can continue to be used ~~for~~at a black-box or ~~a~~ statistical optimizer~~6;~~. In accordance with the present invention, these methods for designing experiments are improved by ~~means of the present invention by virtue of the fact that~~ taking into account prior knowledge or knowledge acquired during the experiment sequence, which speeds up the convergence of the ~~experiments~~methods or actually permits the convergence of the ~~experiments per se.In particular~~optimization methods per se. In a preferred implementation of the present invention, the convergence speed is considerably increased by ~~the~~ tuning according to the invention when, for example, optimizing the ~~designing~~design of experiments for catalysts, active ingredients or materials or reaction conditions. A further advantage is that the number of experiments can be reduced while the same results can be expected, thereby making possible ~~the lower degree of~~a reduced expenditure in terms of time and materials and better utilization of the systems.~~It is also of particular~~ Another advantage is that integrating~~the~~ prior knowledge prevents loss of research investment when HSE or HTS technologies are used alone or in a combinatorial procedure.

~~Figure 3 shows an embodiment of the system for designing experiments in which the experiments are re-evaluated.~~

FIG. 3 shows a system 40 for designing experiments in accordance with an embodiment the present invention including experiment re-evaluation. Referring to FIG. 3, the system 40 includes an experiment set-up module 7 coupled to an experiment data module 8, which in turn is coupled to an evaluation module 10. A meta layer module 9 includes a data analysis module 11 coupled to a rules and conditions module 12, which is coupled to a re-evaluation module 13. The analysis module 11 is coupled to the experiment data module 8 and the evaluation module 10. A black-box optimizer 6 is coupled to the re-evaluation module 13 and an experiment design module 14, which is coupled to the set-up module 7.

~~One~~The system 40 operates as follows. The experiment set-up module 7 performs one or more experiments ~~which have been~~ previously selected from ~~the~~a combinatorial library ~~5 (cf. Figure 2) are carried out in the experiment set-up 7. The corresponding~~(not shown). The module 7 generates experiment data which is output in the form of ~~the~~a data file to the module 8. The experiment data ~~may~~ itself may already contain an evaluation ~~here~~ if appropriate data ~~can be~~is acquired directly by experimental means~~. An example of this is~~, such as by the experimental determination of ~~the~~ yield~~. The yield~~ which is ~~at the same time~~ an evaluation of the experiments ~~carried out~~performed.

~~In other cases~~Alternatively, it may be necessary for an evaluation of the experiment data to be additionally performed in ~~an~~the evaluation module 10. For example, the evaluation module 10 ~~contains~~performs a calculation rule ~~for the calculation of~~process to calculate an evaluation based on one or more of the experiment data. The ~~file~~data in the module 8 and, if appropriate, the result of the evaluation by the module 10 are ~~input into~~provided to the meta layer module 9. The ~~meta layer 9~~

~~contains a~~data analysis module 11 ~~for implementing~~in the module 9 can implement a data mining (DM) algorithm, a neural network~~ or~~, a hybrid method or some other suitable data analysis method.~~Rules are generated~~ The module 12 generates rules by applying such ~~a method, that is to say~~data analysis methods, for example, additional information and observations relating to the understanding of ~~the~~a chemical system considered in the experiments. The module 11 therefore ~~has the function of~~functions as a rule data generator~~. Corresponding rules and secondary conditions are formulated in the module 12 of the meta layer 9.~~, and the module 12 formulates corresponding rules and secondary conditions.

~~A re-evaluation of the~~The module 13, if appropriate, re-evaluates an experiment or experiments~~ is then carried out, if appropriate, in the module 13~~, based on the ~~basis of these~~ rules and secondary conditions~~. This can be carried out in such a way that a re-evaluation of~~ contained in the module 12. In a preferred embodiment, an experiment is ~~carried out~~re-evaluated only if a predefined threshold value is exceeded. Alternatively, the user can ~~also~~ intervene~~ in order~~ to activate or deactivate the re-evaluation. The re-evaluation may ~~consist in experiments which are recognized as being "poor" are given~~include assigning a worse evaluation ~~and~~to experiments ~~which are~~ recognized as being ~~"good" are given~~poor and an improved evaluation~~.On the basis of the file~~ to experiments recognized as being good. The optimizer 6 processes the data in the module 8, which, if appropriate, contains re-evaluated experiment data, ~~the black-box optimizer 6 then creates~~to create a further experiment design ~~18. The corresponding experiments are then in turn carried out in the experiment set-up, and so on.~~which is then representatively stored as data in the experiment design module 14. The experiment set-up module 7 then performs experiments corresponding to the experiment designs stored in the module 14.

~~Figure~~FIG. 4 shows an alternative embodiment ~~in which the filtering is not carried out by means of a re-evaluation of the experiment data, but rather by a preselection~~

~~and/or~~of a system 50 including the feature of filtering data by at least one of pre-selection and weighting. The system 50 for designing experiments ~~in Figure 4 has basically the same design here as that in Figure 3, a module 15 for the preselection and/or weighting being used instead of the module 13.The experiment data is therefore not re-evaluated or evaluated differently, but instead the module 15 can be used, for example,~~has essentially the same component configuration as the system 40, except that the re-evaluation module 13 is replaced by a module 15 for pre-selecting and weighting. Thus the system 50, unlike the system 40, does not re-evaluate the experiment data or evaluate the experiment data in a different manner. Instead, in the system 50, the module 15 operates to eliminate experiments or give them greater or lesser weighting ~~on the basis of the rules determined.~~ based on the rule conditions stored in the module 12. As a result, a ~~preselection takes place~~pre-selection is performed without changing the actual evaluation of the experiments ~~being changed~~.

~~Figure~~FIG. 5 shows a further embodiment of ~~the~~a system 60 according to the ~~invention for designing experiments. The embodiment in Figure 5 differs from the embodiment in Figure 3 and Figure 4 in that there is~~present invention. The system 60 is similar to the system 50, except that the system 60 does not include the module 15. In addition, the system 60 provides for direct intervention into the processing operations performed by the optimizer 6.~~In this embodiment, the~~ Referring to FIG. 5, the system 60 includes an optimizer ~~contains one or more core modules 16, that is to say what are referred to as core operators. In addition, the optimizer 6 contains~~6 containing one or more core operator modules 16 i.e. parts of the program as functions in the algorithms e.g. Selection, calculation of gradients etc.). The module 16 is coupled to the evaluation module 10 and a module 17 for selecting new test points~~. The method of operation of the module 17 is influenced by~~, which is also in the optimizer 6. Further, a post-selection module 18 is coupled to each of the modules 12, 14, 16 and 17.

In operation of the system 60, the rules and secondary conditions formulated by the module ~~12, that is to say, for example, new test~~12 influence the processing performed at the module 17. For example, the module 17, based on the rules and secondary conditions data, rejects new test and points that have been selected ~~by the module 17 are rejected so that there is a feedback from the module 17 to the core module 16 in order to select further, corresponding~~and that are not performing the rules out of module 12 and provides feedback data to the core module 16. The receipt of the feedback data at the core module 16 causes the core module 16 to select test points as replacements for the rejected test points.

After the core module 16 performs actual optimization ~~has occurred in the core module 16 or core modules 16,~~, the module 17, based on data received from the module 16, proposes new experiments or test points for optimizing the target variables of the system under consideration ~~are therefore proposed by means of the module 17. This~~. The system ~~may be~~can include, for example, a chemical, biotechnological, biological or enzymatic system. ~~Experiments which contradict the generated rules are eliminated on the basis of the rules produced by means of the rule generator, that is to say the meta layer 9, and if appropriate said experiments are supplemented with new experiments relating to the optimizer, that is to say the core module 16 or core modules 16.The elimination may be carried out here in a strict way, that is to say completely, or in a soft way, that is to say with a certain degree~~ The rule generator module 12 in the meta layer module 9, based on the rules data generated at the module 11, eliminates experiments that contradict the rules formulated at the module 12. If appropriate, the core modules 16 of the optimizer 6 generate new, replacement experiments. The experiments can be eliminated completely or partially by applying degrees of weighting. The module 17 then acts on these newly designed experiments ~~must then also in turn pass through the module 17. This ensures~~to ensure that information which is not, or cannot~~,~~ be, taken into account by the core ~~module 16 or core~~ modules ~~16,~~16 is

subsequently integrated into the process of designing of experiments~~.~~ in the core modules 16.

Alternatively, ~~a separate~~the post-selection module 18 ~~can follow~~processes data provided by the optimizer 6 ~~in order to perform the~~and performs post-selection of the new test points selected by the module 17.~~This corresponds to a test in the~~ The module ~~18~~18, in other words, performs a test to determine whether the new test points~~,~~ ~~which have been proposed~~ generated by the module ~~17,~~17 conform to the rules~~.~~ provided by the module 12. If test points are eliminated in this test, ~~feedback is in turn necessary in order to design corresponding~~the module 18 provides feedback data to the module 16 to cause the design of alternative new test points.

~~The embodiment of the system for designing experiments in Figure 6 corresponds to the~~FIG. 6 is a system 70 for designing experiments in ~~Figure 5 with the difference that~~accordance with the present invention which is substantially similar to the system 60, except that the module 18 is absent. Therefore, in the system 70, the method of operation of the module 17 is not influenced~~, nor does a~~ by post-selection ~~take place in the module 18, but rather~~processing and, further, the method of operation of the core module~~ 16 or core modules~~ 16 of the optimizer 6 is influenced directly.~~Examples of~~ In preferred embodiments, core operators of neural networks ~~are~~include and consider in the processing the type and number of influencing variables and the weighting of individual data points.~~Examples of~~ In addition, core operators of evolutionary algorithms~~ taking the example of~~, such as the genetic algorithm~~ are the~~, include a selection operator ~~(~~which provides for selection of a new series of experiments~~)~~, the mutation operator and the cross-over operator.

~~The~~In operation of the system 70, the processing at the optimizer 6 accounts for the rules and information ~~which are~~ generated ~~by~~at the rule generator ~~are taken into account in the execution in the algorithm of the actual optimizer.For~~module 12. In a preferred embodiment including optimizers ~~which are~~ coupled to neural networks, ~~this~~

~~means that~~the processing is based on the rules and operates to restrict the experimental space~~ is restricted by the rules~~, or the processing weights the data records ~~are weighted~~ in a particular way.

~~With~~For evolutionary algorithm optimizers, the core operators account for the additional information~~ is taken into account in one or more core operators. This means that, for example~~. In a preferred embodiment, specific cross-overs, selections or mutations are prohibited or ~~carried out~~performed with preference. For both types of ~~optimizer, the result of this is that when there is complete automation of the workflow, there is~~optimizers, intervention into the ~~corresponding program parts~~processing portions of the optimizer~~ via~~, by way of interfaces~~,~~ or ~~the~~including information ~~is included~~ in the optimizer processing by means of manual or program-controlled changes of optimization parameters~~.~~, results in complete automation of the workflow.

~~The embodiments in Figures 3 to 6~~In a preferred embodiment, the features of the systems 40 and 70 can be combined with one another~~,~~ such that~~ is to say~~ a plurality of rule ~~generators, that is to say meta layers 9, can be~~generator modules, in other words, a plurality of meta layer modules, are integrated into the optimization sequence independently of one another.~~ These~~ The rules ~~can be generated~~generator modules generate the rules using various methods~~ which are used independently of one another, and~~, where the methods preferably are independent of one another, and the generated rules are combined in the module 12. The rules~~ which have been~~ formulated by the rule generator ~~or rule generators~~module of the meta ~~layers~~layer module 9 are taken into account either automatically ~~via~~by way of defined interfaces and with compliance with predefined threshold values, or by means of manual formulation of rules for ~~the area~~this part of the optimizer into which the rule generator intervenes.

~~List of reference numerals~~

~~Combinatorial library — 1~~
~~Experiment set-up — 2~~
~~File — 3~~
~~Optimizer — 4~~
~~Combinatorial library — 5~~
~~Optimizer — 6~~
~~Experiment set-up — 7~~
~~File — 8~~
~~Meta layer — 9~~
~~Evaluation module — 10~~
~~Module — 11~~
~~Module — 12~~
~~Module — 13~~
~~Experiment design — 14~~
~~Module — 15~~
~~Core module — 16~~
~~Module — 17~~
~~Module — 18~~

Although preferred embodiments of the present invention have been described and illustrated, it will be apparent to those skilled in the art that various modifications may be made without departing from the principles of the invention.